

APPROXIMATION MODEL BUILDING FOR RELIABILITY & MAINTAINABILITY CHARACTERISTICS OF REUSABLE LAUNCH VEHICLES

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Abstract

This paper describes the development of parametric models for estimating operational reliability and maintainability (R&M) characteristics for reusable vehicle concepts, based on vehicle size and technology support level. A R&M analysis tool (RMAT) and response surface methods are utilized to build parametric approximation models for rapidly estimating operational R&M characteristics such as mission completion reliability. These models that approximate RMAT, can then be utilized for fast analysis of operational requirements, for lifecycle cost estimating and for multidisciplinary design optimization.

Introduction

A significant portion of life-cycle costs for many complex systems, such as reusable space transportation systems, is generated during the operations phase. Studies indicate that operations costs for reusable launch vehicles can account up to 70 % of the total life-cycle costs [1]. These costs are largely determined by decisions made during conceptual design. As a result, operational considerations need to be modeled and studied early in the design phase. This is a challenging task since operations and support requirements estimation for new space transportation system concepts is characterized by high uncertainty mainly due to lack of historical data. Furthermore, research and studies for developing simulation models in the operations area has been limited.

Modeling Operational Requirements

Operational requirements for space transportation systems can be linked to the concept through its reliability and maintainability (R&M) characteristics and studied using simulation. These characteristics for a future launch vehicle design can be estimated based on comparisons to existing systems. For this purpose, a reliability and maintainability analysis and estimation tool (RMAT) which is based on comparability to support requirements for current operational aircraft and launch vehicles has been developed [2, 3]. Using RMAT, operational characteristics such as mission completion reliability, maintenance actions per mission, manpower and support requirements can be estimated for a particular vehicle concept and mission scenario.

The next step is to utilize these operational characteristics for systems level study of design concepts and for life-cycle operational resource estimation. However, RMAT is a complex, stand-alone, operational analysis code requiring expert user inputs. As it currently stands, it is very difficult to integrate RMAT with other disciplinary analysis codes for use directly for systems level optimization and simulation studies. If, however, one can express operational performance characteristics (y) such as mission completion reliability as a function of certain input parameters (x_i) in a mathematical model that approximates RMAT results, operational analyses and optimization studies can be conducted more rapidly.

The purpose of this study is therefore, to develop approximation models, called response surface models,

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for estimating R&M performance characteristics for a range of reusable launch vehicle concepts based on vehicle size and technology support level. RMA and design-of-experiments based response surface methods for parametric model building are utilized to sample the design space efficiently. Using the data generated, second-order response surface models are constructed that approximate the launch vehicle R&M performance characteristics using multivariate regression analysis techniques, both at the vehicle and subsystem levels. These R&M models that approximate RMA for characteristics such as mission completion reliability and total maintenance actions, can then be utilized for fast analysis and simulation of operational requirements for a variety of vehicle concepts. The main advantage is that the parametric models may enable the rapid estimation of operational resources early in the design phase for life-cycle cost analysis and systems level design integration of operational requirements for MDO. This study has the following steps:

Model Parameters

The first step was to identify the most influential R&M input parameters to be included in the response surface model for a launch vehicle design concept. Eight input parameters (x_i) that described a wing-body, single-stage-to-orbit launch vehicle concept were determined to be included in this study. These were,

1. Dry weight,
2. Body length,

3. Wing span,
4. Number of engines,
5. Mission duration,
6. Total vehicle wetted area,
7. Fuselage area,
8. Fuselage volume.

By varying the values of these input parameters within their feasible range, many different size launch vehicles can be described (from small to large) depending on the technology support level. The output performance characteristics (Y) modeled were:

1. Mission Completion Reliability,
2. Total Maintenance Actions,
3. Unscheduled Work Hours,
4. Scheduled Work Hours,
5. Earned Manpower.

The objective now is to construct response surface models that approximate RMA in the form of $Y = f(x_i)$ at vehicle and subsystem levels.

Vehicle Design Matrix

The goal in this study is to use these models to estimate an output performance characteristic at the vehicle level rapidly in terms of the eight input parameters for a range of values that form a matrix for the wing-body, single-stage, launch vehicle. This matrix of vehicle designs based on size (from small to large) and technology support level is outlined in Figure 1.

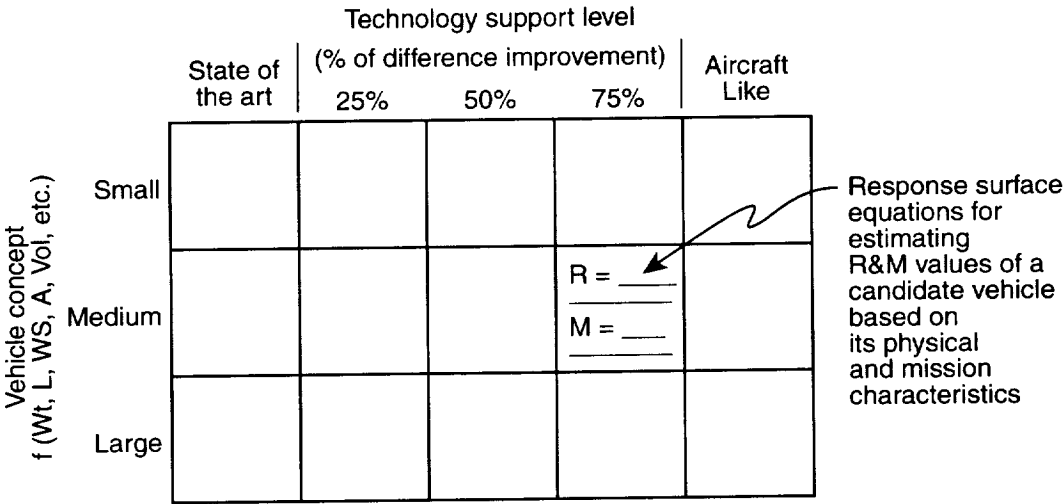


Figure 1: Vehicle designs based on size and technology support level.

The technology support levels range from “state-of-the-art” to “aircraft like”, where the vehicle is expected to operate like an aircraft. For each of the vehicle definitions in the matrix, a corresponding RMAT model was developed both at the vehicle and subsystem levels. The subsystems modeled were propulsion, thermal protection and structures.

Technology Support Levels

The determination of technology support levels is based on the expert opinion of vehicle design engineers and operations personnel. A questionnaire was developed and experts at Langley Research Center (LaRC), Marshall Space Flight Center (MSFC), and Kennedy Space Center (KSC) were surveyed to determine which vehicle characteristics will have the greatest impact on the operations and support requirements.

The survey consists of four sections including a vehicle systems level section and sections for the three subsystems to be modeled. Each section contains a series of parameters that may impact overall operations and support requirements. For each parameter the expert is asked to indicate the impact of the parameter on support requirements for that system. Under each parameter there is a series vehicle attributes that may impact that parameter. For each attribute the expert is asked to assess the percent improvement (or detriment) that the attribute will have on its parameter. In addition, the expert is also asked to indicate how confident they are in their assessment. The attribute’s impact and confidence are combined to determine attribute’s final level of improvement. In the model’s final form, the vehicle’s attributes will be the basis for determining a vehicle’s overall improvement in operations and support requirements.

Response Surface Model

Polynomial approximation models have been commonly used in response surface model building since in many cases they can provide an adequate approximation, especially if the region of interest is sufficiently limited. A quadratic response surface model has the form

$$y = b_0 + \sum b_i x_i + \sum b_{ii} x_i^2 + \sum \sum b_{ij} x_i x_j \quad (1)$$

where, x_i are the input variables that influence the response (operational output characteristic such as vehicle reliability) y , and b_0 , b_i , and b_{ij} are estimated model coefficients. The cross terms represent two-parameter

interactions, and the square terms represent second-order non-linearity.

There are various techniques that may be utilized to sample the design space efficiently for constructing polynomial response surface models. Some of these are, central composite designs [4, 6, 7], D-Optimal designs [8, 11], and orthogonal arrays for computer experiments [5, 9, 10]. Response surface methods using these designs have been applied to various multidisciplinary design optimization problems [10-17]. The main advantage is that, response surface methods can aid multidisciplinary design integration, and provide rapid design analysis and optimization capability in many applications. However, constructing response surface models can get inefficient as the number of design variables studied increase and in some applications the polynomial models may be inadequate in approximating a complex response surface.

For this operations modeling study, an “expanded” central composite design (CCD) was chosen mainly due to its simplicity and due to fact that each RMAT run required only a few seconds of computer time for the vehicle concept studied. An expanded CCD in this case is two central composite designs one imbedded within the other. This approach resulted in an experimental design that is more “space filling” [10] than a standard small CCD where most of the sampling is concentrated at the outer edges of the design space. As an example, Figure 2 illustrates the combinations of settings for a standard CCD and an expanded CCD for two parameters, x_1 and x_2 . The first design has 8 runs at the edges of the design space and a center point. The second design illustrating an expanded CCD has additional 8 points in between the 8 runs and the center point. Even though about twice the number of runs are required with this expanded design, it enables a more thorough sampling of the design space. The disadvantage is that about twice the number of runs required with an expanded CCD. This approach can become prohibitive for vehicle concepts that may require more computer time to analyze.

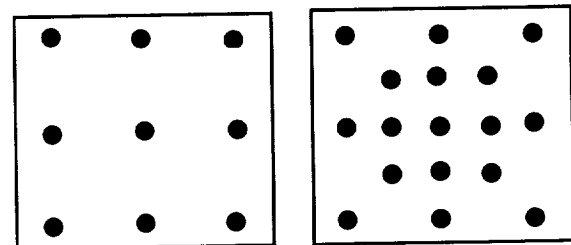


Figure 2: Two parameter CCD and Expanded CCD.

Table 1: Expanded Central Composite Design

	Dry Weight	Length	Wing Span	No. of Engines	Mission Length	Wetted Area	Fuselage Area	Fuselage Volume
1	-2	-2	-2	-2	-2	-2	-2	2
2	-2	-2	-2	-2	-2	2	2	-2
3	-2	-2	-2	-2	2	-2	2	-2
4	-2	-2	-2	-2	2	2	-2	2
.
159	0	0	0	0	0	0	1	0
160	0	0	0	0	0	0	0	-1
161	0	0	0	0	0	0	0	1

In this application, the expanded CCD constructed for eight variables (Table 1) has 161 rows (requiring 161 design points or analysis code iterations) as opposed to a small CCD design having 81 rows. Each design variable range was transformed to five coded values ranging from +2 (high value), to -2 (low value) [4, 6]. The model coefficients were derived using these coded values. Therefore each of the eight input parameters are studied at five levels (values) represented by, -2, -1, 0, +1 and +2 in coded form.

As an example, for a small, state-of-the art vehicle, the dry weight range given by the design engineer was from 111, 991lb to 136,877 lb. In coded form -2 corresponds to 111,991 lb, -1 corresponds to 118,213 lb, 0 corresponds to 124,434 lb, +1 corresponds to 130,655 lb and +2 corresponds to 136,877 lb.

Using this modified CCD design, corresponding RMAT runs were made at 161 different combinations of the eight input parameter values for each of the 25 different vehicles sizes ranging from small to large (Figure-1). Therefore, $161 \times 25 = 4,025$ RMAT runs were made for each vehicle and subsystem definition. The output values for Vehicle Mission Completion Reliability, Total Maintenance Actions, Unscheduled Maintenance Hours, Scheduled Maintenance Hours and Earned Manpower were recorded for each combination.

Construct the Second-Order Models

In the following step, operations output data and multiple regression analysis were used to construct second-order response surface models in terms of the eight input parameters.

An example output table is given in Table 2 which displays the results for mission completion reliability,

total maintenance actions and unscheduled maintenance hours for a given set of input parameter values in coded form. Least squares multivariate regression fit was very good in all cases with adjusted-R-square values ranging from 0.98 to 0.99, with low model mean square errors.

Table 2: Sample Results

	Coded
Dry Weight	2
Length	2
Wing Span	2
No of Engines	2
Mission Length	2
Wetted Area	2
Fuselage Area	2
Fuselage Volume	2
<i>Mission Reliability</i>	0.99868
<i>Total Maint Actions</i>	19
<i>UnScheduled Maint Hrs</i>	148
<i>Scheduled Maint Hrs</i>	44

The second order response surface models were constructed for each of the vehicle definitions and technology levels. The analyses were repeated at subsystem levels for propulsion, thermal protection and structures. These models could now be used to quickly determine the effect of varying input parameter values on the output performance characteristics for the range of vehicles described by the matrix. Sensitivity simulation studies can be carried out without the need to re-run RMAT after each change.

Conclusions

This paper described the development of response surface models for estimating reliability and maintainability (R&M) characteristics for a range of reusable launch vehicle concepts at various technology levels ranging from state-of-the art to aircraft-like systems. An expanded central composite design was utilized to sample the design space and build second order approximation models both at vehicle and subsystem levels.

Even though about twice the number of RMAT runs were required with the expanded CCD design (as opposed to a traditional small CCD), it was preferred since it enabled a better sampling of the design space and since each RMAT run could be made reasonably quickly. If, however, vehicle concept complexity increases and RMAT runs should require more computer time, orthogonal arrays may be utilized instead of the expanded CCD to reduce the number of design points needed. Reference [9] presents an approach to construct orthogonal array (OA) based Latin Hypercube designs (LHD). OA based LHD for computer experiments have an appealing "space filling" property [10] which enable a more thorough sampling of the design space, requiring about the same runs as a traditional small CCD would.

A major advantage of developing the response surface approximation models for estimating R&M characteristics for a range of vehicle concepts is that they may lead to rapid estimation of operational resources early at the design phase for lifecycle cost analysis. These response surface models also may enable the integration of operational considerations to the overall conceptual vehicle design process through the use of mathematical programming methods for rapid multidisciplinary design optimization.

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